

# Dynamics of Opinions and Social Structures

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Social groups with widely different music tastes, political convictions, and religious beliefs emerge and disappear on scales from extreme subcultures to mainstream mass-cultures. Both the underlying social structure and the formation of opinions are dynamic and changes in one affect the other. Several positive feedback mechanisms have been proposed to drive the diversity in social and economic systems (1, 2), but little effort has been devoted to pinpoint the interplay between a dynamically changing social network and the spread and gathering of information on the network. Here we analyze this phenomenon in terms of a social network-model that explicitly simulates the feedback between information assembly and emergence of social structures: changing beliefs are coupled to changing relationships because agents self-organize a dynamic network to facilitate their hunter-gatherer behavior in information space. Our analysis demonstrates that tribal organizations and modular social networks can emerge as a result of contact-seeking agents that reinforce their beliefs among like-minded. We also find that prestigious persons can streamline the social network into hierarchical structures around themselves.

The competition between segregation and coherence in social systems has long been a subject of both practical and theoretical interest. T. Schelling proposed simple models to understand how segregation emerge in urban areas (3) and B. Arthur suggested that the emergence of industrial centers is a result of positive feedback between agencies that prefer to be close to similar agencies (1). In general, the goal of individuals to understand and agree with their closest associates (4, 5, 6) can be obtained by either merging opinions with friends or by creating new contacts. In this spirit, we will discuss a social network model where individuals can use their connections to communicate and update their views with friends or establish new contacts via friends to shortcut communication pathways. By modeling communication on the network and adaptive rewiring of the network together, we reveal strong reinforcement of opinions in emerging group structures.

To comprehend the dynamics of opinions in a social system, it is important to understand the coupling to the social structure the dynamics is embedded in (6, 7, 8, 9). For example, if anyone shares information with anyone else without any preference, the society can be described by a simple mean-field model where everyone has access to all information. On the other hand, if people only interact with a small number of friends, the description of the system must reflect this communication constraint. A network representation of the interactions in the system is a powerful way to depict the limited access to information; a static network with exchange of information between and about nearest neighbors alone represents a scenario with the most limited access to global information. Which world do we live in?

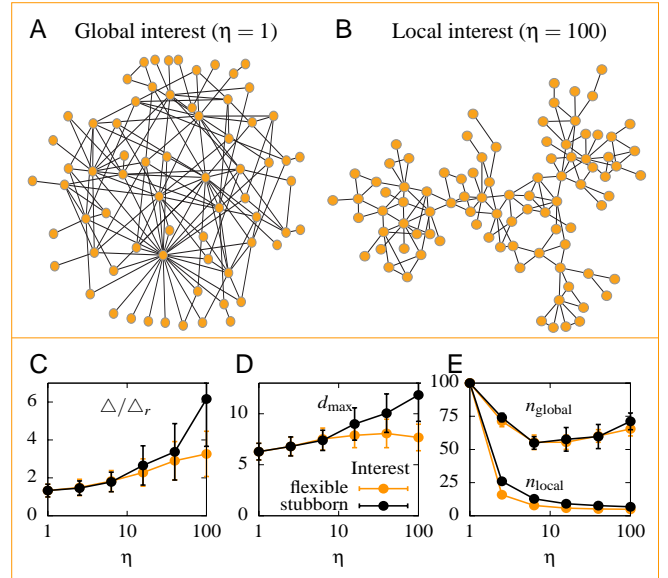


FIG. 1 Interplay between network structure and the extent  $\eta$  to which recent gossiping influences the priority in social climbing. Varying  $\eta$ , the bottom pane illustrates cliquishness (C), diameter (D), and social horizon (E). Simulations based on  $C = 10$  communication events per link for each rewiring event in the system with system size fixed to  $N = 100$  and  $L = 150$  links. The results are robust to a hundred-fold drop in the communication to rewiring ratio, but break down at an even lower communication rate when only small groups can be maintained by the communication. Panels C-E also illustrate the dependence of the rate of opinion adaptation, flexibility, with stubborn adaptation referring to a  $\mu = 0.01\%$  change of the interest elements per communication event, and flexible referring to  $\mu = 1\%$  change. We define the flexibility as  $\mu CL$ . Stubborn adaptation corresponds to a flexibility of 15% changes in all interest memory when all links are changed once whereas flexible adaptation corresponds to complete reallocation.

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Taking the latter perspective, an immense literature on opinion formation on static networks, most straightforward formulated in the voter model (10, 11), has helped us understand how the structural constraints affect the dynamics. In this letter, we take a different approach and instead ask where the preference for specific information comes from and how the network constraints can be overcome to make this information accessible.

To open up the world beyond nearest neighbors, we present a game in which we let agents improve their positions in a dynamic network based on their limited local perception of the system. To maintain this perception, they continuously communicate to obtain (1) a picture of where other agents are in the network and (2) an opinion about the importance of other agents. We incorporate information flows from distant parts of the social network into the model by letting two connected agents communicate and share information about any third agent in the network. This indirect information-gathering resembles the frequent gossiping in daily life and its consequences for non-local information assembly has been investigated in static social networks (12).

To incorporate the above elements in a simple model, we give each agent an individual memory. The memory includes three vectors with (1a)  $N$  pointers associated to the  $N$  agents in the system that show which friend provided information about the agent, (1b) the age of each of the  $N$  pieces of information to compare the quality of the information with friends, and (2) the names of other agents filling the memory to an extent that reflects the interest in these agents. The memory in (1a) and (1b) is a map and (2) is the priority.

We emphasize that all agents have a pointer, an age of this pointer and a priority for each other agent in the system. The pointer and its age in itself is enough to allow communicating agents to build an operative map (13) of their own position in the network as described below. With the priority memory, we can incorporate simplified human behavior by introducing rules that mimic individuals' choices when selecting who they want to connect to or talk about. This makes it possible to explore the mechanisms behind the emergence opinions among individuals.

The memory is updated through communication over links in the network, which in turn are rewired based on the locally obtained knowledge. Because of the ongoing changes in the social network, the obtained knowledge becomes outdated with time. Accordingly, when two agents communicate about a third agent, they first decide which of them that has the newest information (13). This information is considered the most reliable, and the agent with the older information updates its information using the agent with the newer information as a reliable source of information about the third agent. We increment the age in (1b) for all agents when every link has participated in on average one communication event in the system. Because every agent always has information with age 0 about itself, the age of the information about an agent will tend to get older the further away it is from the agent in the network. The age of the information is therefore a good proxy for its quality, assuming that agents are not lying.

The basic model, accessible as a Java applet with a detailed

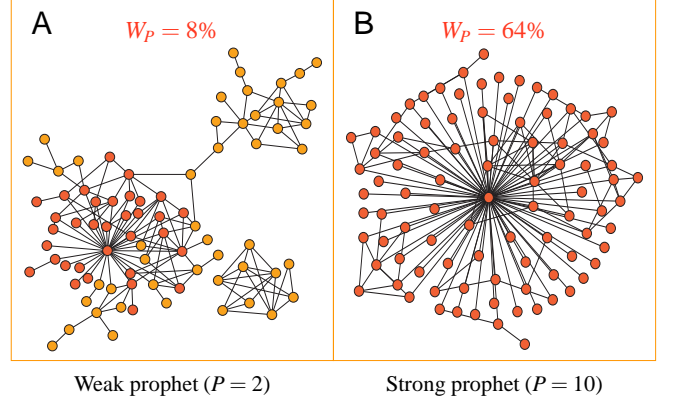


FIG. 2 Network structures where one agent, the prophet  $P$ , has increased prestigious power to capture an unusually large fraction of the memory of whoever she talks to. The results are based on a prophet with (A) weak prestige  $P = 2$ , and (B) high prestige  $P = 10$ . Note that when sub-networks separate entirely, as in panel A, the agents still maintain information about who they should contact in the social climbing step and separated clusters can reconnect. The  $W_P$  values correspond to the fraction of global interest devoted to the prophet. Other parameters as in Fig. 1B.

description (14), is defined in terms of  $N$  agents with a fixed number  $L$  of links. The network model is executed in time steps, each consisting of one of the two events:

- *Communication C*: Chose a random link and let the two agents connected by the link communicate about a third agent *selected* by one of them. The two agents also update their information about each other.
- *Social climbing R*: Let a random agent use the local information to form a link to a friend's friend to shorten its distance to a *selected* third agent. Subsequently a random agent loses one of its links.

Communication or gossiping involves evaluation of information quality based on its age as described above. The social climbing, which corresponds to rewiring of the network, is a slow process compared to gossiping. If this was not the case, random people would share reliable information with anybody and the interactions could be simpler described by a mean-field model. We therefore simulated the model with 10 communications per link for each rewiring event in the system. Links are formed to friends of friends similar to triadic closure (15), reflecting a gradual social climbing. Here friends refer to the particular agents that have provided the most recent information about the selected agent. The new links are therefore formed on basis of the memory rather than on basis of the present network (16).

To be able to investigate the reinforcement of opinions, we vary the way we specify the selection criterion for the third person, the agent of interest, in the communication and the social climbing events. Figure 1A and B illustrate that two different selection mechanisms can give rise to widely different social networks. To generate the network in Fig. 1A, we let the agents select the agent of interest randomly with equal

chance for any agent. In contrast, to generate the modular network in Fig. 1B, we let one of the communicating agents use her prioritized memory to select the agent of interest (in a communication event we always let the other agent passively accepts the choice). Following Spencer’s (17) observation of proportionality between interest and previous experience, an agent’s priority memory is filled with other agents’ names proportional to their occurrence in the agent’s recent gossiping. Related to this use of proportionate selection is the work by H. Simon (18) to explain Zipf’s law and the work presented in refs. (19, 20) to model emergence of fashions.

The priority memory is essential for modular structures to emerge. Let us therefore describe in more detail how we implement the proportionate selection when building the priority memory for each agent. We regulate the extent to which agents select the topic of conversation according to recent gossiping by the external parameter  $\eta$ , which may also be understood as the ratio of local to global interest. For each agent  $j$ , we model the priority memory in (2) above by  $N\eta$  elements. The first  $N$  elements are static and fixed to each of the  $N$  agents’ names corresponding to the global interest. The remaining memory can be changed by communication. When agent  $j$  talks to, or hears about, another agent  $i$ , the name of  $i$  will randomly replace a fraction  $\mu$  of this memory. Old priorities will thereby slowly fade as they are replaced by new topics of interest.

In selecting communication topic or aim of social climbing, agent  $i$  is chosen with probability  $w_j(i) = n_j(i)/(N\eta)$  proportional to how many times the name of  $i$  occurs in agent  $j$ ’s priority memory,  $n_j(i)$ . The size of  $\eta$  determines the degree of preferential allocation of memory. For  $\eta = 1$  any topic is selected with equal chance (global interest, see Fig. 1A), whereas larger  $\eta$  increases the chance that the agents choose a topic proportionate to personal experience (17) (local interest, see Fig. 1B).

A dominant local interest with large  $\eta$  predicts an evolving network with pronounced modular structure as in Fig. 1B. The emerging modular network does no longer develop large hubs, but instead shows large cliquishness quantified by the number of triangle motifs in units of the random expectation (21),  $\Delta/\Delta_r$  (see Fig. 1C). Figure 1D shows that the diameter  $d_{\max}$  of the network easily doubles as  $\eta$  increases, weakening the small-world effect (22) and the global navigability of the network (23) (to illustrate the robustness of the model, we in Fig. 1C-E show the results for two different opinion adaptation rates  $\mu$ ).

To quantify the locally acquired interest we counted the effective number of persons,  $n_{\text{local}}$ , a typical agent has in the interest memory

$$n_{\text{local}} = \left\langle \frac{1}{N \langle w_j^2(i) \rangle_i} \right\rangle_j. \quad (1)$$

Here  $\langle w_j^2(i) \rangle_i$  averages over the weights allocated to different interests  $i$  of agent  $j$ . Figure 1E shows this social horizon of the individual agent,  $n_{\text{local}}$ , as well as the global horizon where all memories are pooled together in  $n_{\text{global}}$  (24). As  $\eta$  increases,  $n_{\text{local}}$  collapses while  $n_{\text{global}}$  remains on the scale of  $N$  — the development toward social cliques is democratic, with

anyone getting a fair share of attention while still allowing people to focus locally on members of their particular “club”. The extent to which this club is maintained and closed for migration is controlled by the flexibility defined in the caption of Fig. 1; the modular structure breaks down when one changes opinion faster than one changes friends.

We would like to emphasize that our model presents a *spherical cow* of human memory and response quantified through 3 parameters: the communication level  $C$ , the local to global interest  $\eta$ , and the flexibility  $\mu$ . For  $C$  sufficiently high, our results are independent of further increase in communication. At any reasonably low level of flexibility  $\mu$ , the evolving system develops a modular structure and a diminished information horizon with increased  $\eta$ . Thus the model emphasizes the proportionate interest allocation (17, 18) as the key parameter for development of segregation.

Our idealized model-world consists of agents with equal properties. In spite of this equality, the model predicts segregation in the form of a social network with modular structure with widely different priorities and opinions. The local agreement and global divergence self-organize as a consequence of repeated recent communication and reinforced contacts to people one gossips about.

Central to the model is to build and use the priority memory. Here we have explored a particularly simple linear model for both the construction and the use of priorities. But we stress that the model framework can be extended to more detailed networking games, including for example trust (25), cheating agents (26), or update of priorities based on experiences of the reliability of the obtained information. Undoubtedly, real humans will have different intrinsic properties. As the simplest example of how heterogeneous agents may influence the system, we will study the case where one agent has one special property.

We consider a simple directed strategy to influence public opinion aimed to increase the status of a particular agent.




- *Prophet P*: each time agent P communicates, she imposes her personality on the agent  $j$  she talks to by converting a fraction  $P\mu$  of this agent’s interest memory to P.

The “prophet” uses the local network structure in analogy to the way the so called “heroes” or social leaders have influenced the society with their acquired prestige (27, 28, 29).

The spreading of information across the system is analogous to viral marketing (30), which makes it possible for the prophet to reinforce her position by gaining visibility and subsequently links from larger parts of the system. Moreover, higher connectivity makes the prophet preferentially more accessible to people and the prestige-biased transmission of ideas (29) modeled by the priority memory connects the positive feedback. When  $P = 1$  the prophet P becomes a normal agent, and the overall network develops to resemble the one in Fig. 1B. Figure 2 shows that an agent’s increased ability to positively bias other persons’ interest memories drives the network topology toward a centralized structure. For example, a single prophet with strength  $P = 2$  can

generate a substantial group of followers (Fig. 2A). The figure also illustrates that separated social groups can emerge and collapse by temporarily weaker interest in other agents. Figure 2B shows that a strong prophet drives the full system to a single hierarchical structure. In fact, by measuring the social horizons we find that a single P with strength  $P = 10$  drives both  $n_{\text{local}}$  and  $n_{\text{global}}$  to about 2 — a dominating prophet can efficiently initiate a totalitarian system to an extent that people barely think about anybody except the social leader. This facilitates social coherence and order, but obviously not the formation of diverse cultures or coexistence of small communities.

In general, the emerging structures are robust consequences of an interplay between the following positive feedback mechanisms:

- 1) Network centrality: being central  new information.
- 2) Positive assortment: agent's opinion  neighbor's opinion.
- 3) Segregation: move toward opinion  localization of opinion.

Without individuals with personal interests only the first feedback is active, but is in itself enough to give the network a broad degree-distribution (26). The two subsequent reinforcements generate interest groups and segregation manifested in a modular network. Together these feedbacks make it very favorable to manipulate opinion spreading. Here we have presented a framework which can give insight into the mechanisms of communication strategies in historical as well as modern propaganda.

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